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THE EFFECT OF UNEMPLOYMENT BENEFITS ON HEALTH AND LIVING STANDARDS IN TURKEY: EVIDENCE FROM STRUCTURAL EQUATION MODELLING AND REGRESSION DISCONTINUITY DESIGN[1]

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Abstract

Unemployment can negatively affect individuals, their families and communities in various ways. When individuals are out of work may experience mental and physical health problems, material deprivation and poverty. This study aims to examine the impact of unemployment benefits on health and living standards in Turkey. We employ a structural equation modelling (SEM) to take into account the simultaneous relations among the latent variables of health and Standard of Living (SoL). Additionally, we propose a fuzzy Regression Discontinuity Design (FRDD) within the SEM framework to infer for causality. For the empirical analysis we use the panel Income and Living Conditions Survey (ILCS) over the period 2007-2015. Our findings suggest that those who receive these benefits are more likely to report higher levels of health and improve their living standards compared to the non-recipients. Our results indicate a large heterogeneity on the impact of unemployment benefits, as males, low educated individuals and those belonging in the lower levels of income are affected more in terms of their health status and living standards. The majority of earlier studies have focused on the impact of unemployment benefits on labour outcomes. The originality of this study is that we implement the FRDD within the SEM framework to explore simultaneously the impact of unemployment insurance on heath and living standards. Moreover, this framework can be applied in future research studies to infer causality and explore the impact of policies and reforms.

Keywords: Fuzzy Regression Discontinuity Design; Health Status; Standard of Living; Structural Equation Modelling; Unemployment Benefits.

JEL Classifications: I14, I31, J21, J38.

1. Introduction

Following the financial crisis of 2001, persistent high unemployment rates was one of the main challenges in Turkey. Even though, the Turkish economy has experienced a good performance in terms of economic growth, the unemployment rate has increased from 5.6 percent in 2001 to almost 10 percent in 2002 and remained high since then (Tiryaki and Khakimov, 2009). During the great recession of 2007-2009 the unemployment has even reached the 13 percent, reduced at 8.2 in 2012, reaching 10.5 percent in 2018 (OECD, https://data.oecd.org/turkey.htm) and 13.8 percent in July of 2020[5].

It is well-recognised by the majority of the countries that unemployment benefits provide an insurance and consumption smoothing, helping to restore a part of the wealth loss and to improve their health status, which is very unlikely to be provided by the private markets. On the other hand, unemployment benefits can be also associated with distortion incentive related costs of looking for another job. However, this will strongly depend on the allowance amount, its proportion and share of the total household income and the unemployment duration.

The aim of this study is to explore this impact, using detailed micro-level data derived by the Income and Living Condition Survey (ILCS). Unemployment benefits, health and living standards are the variables in the analysis affecting each other simultaneously and the relationship among those in earlier studies is not thoroughly examined within the system of simultaneous equations as we aim to address here. The study is motivated by the need to understand how the unemployment benefit policies influence individuals' health and living standards. In particular, one might assume that unemployment benefits may reduce the fear of job loss associated with labour market fluctuations, while the unemployed may act as stabilisers for the consumption smoothing affecting living standards. Even though the unemployment benefits are not explicitly designed to alleviate the financial stress of job loss, they could have also unintended positive effects on health. More specifically, if income loss and financial insecurity are parts of the detrimental effects on health, then unemployment benefits may be a mechanism to prevent or reduce some of the negative health effects of job loss. There are various ways in which standard of living and health may interact.

First, poor health will decrease the living standards of a person as they have to spend more money on goods and services to alleviate the effects of their health status. Second, poor health will reduce the amount of paid work a person can do, or restrict the type of work they can do, decreasing their earnings. Thus, people with poor health conditions may remain in the labour force, but their capability and productivity is severely impaired, affecting their living standards.

[5] https://data.oecd.org/unemp/unemployment-rate.htm

The Structural Equation Modelling (SEM) employed is useful to explore, not only the effect of unemployment benefits on health, and living standards, but also the relationship of health, and poverty with other socio-economic characteristics. Apart from that, it is also possible to stand out with the methodological contribution, which refers to the regression discontinuity design (RDD) allowing to establish and maximize similarities to experimental designs using surveys and comparing the health and living standard levels between the case group, consisting of the individuals receiving the unemployment benefits and the control group, which is individuals who do not receive any unemployment allowance.

The structure of the paper is as follows: In section 2 we discuss briefly earlier studies of the unemployment impact on health and living standards. In section 3 we describe the methodology followed in the empirical analysis and the unemployment benefits policies in Turkey. In section 4 we present the data and surveys used in the empirical work. In section 5 we report the main findings and in section 6 we discuss the main concluding remarks of the study.

2. Literature Review

Various studies have explored the relationship between employment and health outcomes, both mental and physical and the role of the socio-economic status, such as education, professional class, and working skills and experience (Saunders, 2002; Saunders and Taylor, 2002; McLean et al., 2005; Marmot and Wilkinson, 2006). It has been revealed that the loss of income caused by unemployment, financial tightness and even poverty and many psychological diseases, as well as, physical health problems are brought together. Inadequate nutrition, inability to live in good conditions and mental depression are the main reasons for the emergence of health problems. It is found that unemployment is not only caused by loss of earnings, but also by removing the individual from the working environment and by reducing social interaction with other individuals. Studies support that social phobia, which occurs in individuals with reduced social sharing, brings along mental health problems. It is found that the decrease in social communication leads to self-confidence weakness in individuals, loss of status as a result of being unemployed and friends and relatives and triggers individual well-being and health problems (Björklund, 1985; Mayer et al., 1991; Björklund and Eriksson, 1998; Helliwell and Putnam, 2004).

Studying and having a job is a life therapy, but reverse unemployment is a health issue (Waddell and Burton, 2006). Karsten and Klaus (2009) analysed 237 horizontal-cross sectional data and 87 panel data studies on the relationship between unemployment and mental health through a meta-analysis method. The meta-analysis results of the cross-sectional studies revealed that unemployed individuals had more mental distress and health disorders than those who continued to work. The meta-analysis of panel data studies showed that while losing a job has negative effects on mental health, re-recruitment decreases this negative impact over time. Kroll and Lampert (2011) analysed the relationship between unemployment, social support and physical, emotional and functional disorders in working age individuals in Germany. Using the GEDA (Gesundheit in Deutschland Aktuell) data set in Germany in 2009, the authors found that unemployment is closely related to these problems and complaints. Heggebø (2016), using the European Union Income and Living Conditions Micro Data Survey and applying the generalized least-squares method, analysed the health impact of the unemployment situation in Denmark, Norway and Sweden in 2007-2010 as a result of the great recession. Their findings pointed to Denmark as the only Scandinavian country in which the health status of the unemployed was worsened. Wang (2015) empirically estimated the short-term and long-term effects of the unemployment rate on health in China and found that a 1% decrease in the unemployment rate results in a 4% reduction in mortality. In the long term, it is also revealed that a 1% increase in unemployment rate will cause an increase in unemployment rate of 6.8%. Other studies have shown that unemployment has a great negative impact, not only on the unemployed individuals, such as material deprivation, mental and physical health problems, but also on other individuals in the household and the society on the whole (Bradshaw et al., 1983; Raphael, 2001; Johnson and Feng, 2013).

Considering the loss of income, which is one of the most important effects of unemployment, and the living standards and health status that it adversely affects, it is seen that supporting individuals with unemployment benefits is an important policy. Although unemployment benefits vary from country to country in terms of allowance amount, payment terms and number of eligible people, these benefits can be valuable to beneficiaries in terms of three common aspects (ILO, 2000). First, beneficiaries are living a healthier life than those who do not benefit, however, they should share similar characteristics, but for certain reasons are ineligible. The second aspect is to ensure that individuals can maintain their living standards at a certain level. The third aspect is to increase the likelihood of employment and to allocate individuals to the appropriate job in accordance to their skills and training.

Various studies have employed the RDD investigating the impact of unemployment benefits on labour and health outcomes. For instance, Schmieder et al. (2016) have employed a sharp RDD and instrumental variables approaches and they find that each additional month of unemployment insurance non-employment duration for middle-aged workers leads to a statistically significant reduction in wage offers of 0.8 percent. Similarly, Lalive (2007) used a RDD framework to explore the impact of unemployment benefits on various labour outcomes in Austria. The findings indicate that large extensions of the benefits reduce the transition to a regular job and increase the unemployment duration, but have not noticeable impact on the quality of the post-employment job measured by the earnings in the new job. On the other hand, small extensions in benefits do not increase unemployment duration for men. The study by Kyyrä and Pesola (2020) using a regression kink design (RKD) shows that the wage in the first job following unemployment and also the subsequent earnings in the two years after the beginning of the unemployment spell decrease with the levels of unemployment benefits. A similar study to our is by Shahidi et al. (2019) who found that the unemployment benefits may reduce the probability of reporting poor self-rated health by almost 5 percent. Moreover, the sensitivity analysis shows that the treatment effects are stronger among lower income and less educated persons, while small or even negligible effects are reported among high income and educated individuals.

To the best of our knowledge, there is no study exploring the simultaneous relationship among unemployment benefits, health and living standards establishing a causal inference as this study attempts to do. The study by Ozdamar and Giovanis (2017) explores the impact of survivor benefits on health and poverty in Turkey, while Bilgiç and Yılmaz (2013) explore the relationship between financial aid and the psychological health among Turkish unemployed people. However, these studies do not employ regression discontinuity designs or structural models, as we aim to incorporate the FRDD within the SEM framework that allows to infer causality and to explore the relationship between unemployment benefits and the latent variables of health and living standards. In particular, we aim to explore whether the unemployment benefits not only smooth the consumption during periods of unemployment, but also to explore whether they may affect health.

3. Methodology

3.1 The Turkish Unemployment Insurance Scheme

The eligibility for the unemployment insurance in Turkey, refers to employees, including foreign nationals, aged 18 or older working in the private or public sector. This excludes individuals working in the agriculture and forestry sector, self-employed, students and military personnel. The unemployment benefits provide the 40 percent of the daily average gross earnings and cannot exceed the 80 percent of the gross monthly minimum wage. The reference period for the eligibility is the past three years before job loss. The required minimum employment record is 600 days and of these at least 120 days must have been accumulated in the past year. The payment period varies according to the days of contributions. More specifically, an insured individual who has at least 600 days of contribution is eligible to receive the unemployment benefits for a period of 180 days. In the case of 900 days of contribution, the period of payment rises at 240 days, and if the insured person has contributed 1,080 days then she is entitled for a payment period of 300 days (OECD, 2018).

3.2 Structural Equation Modelling (SEM)

In this section we describe the methodology applied in the empirical analysis. Structural Equation Modelling (SEM), is a system of equations that uses latent variables and models multivariate relationships (Goldberger, 1973; Bollen, 1989). SEM consists of the measurement model, which includes the latent variables that are not directly observable. The SEM employed in the study is represented by equations (1)-(5). In this context, the first stage of the SEM process includes the estimation of the latent variables health and standard of living. The observed variables used to construct these latent variables are reported in the data section. In particular, the two latent variables employed in the empirical analysis are measured using the related survey questions.

$$h_{it} = \mathbf{\Lambda_h} H_{it} + \varepsilon_{it}^{h} \tag{1}$$

$$s_{it} = \mathbf{\Lambda_s} SoL_{it} + \varepsilon_{it}^{s} \tag{2}$$

Equation 1 is the measurement model for the health latent variable *H* which relates the observed variables *h* used to contruct the health index in the factor loadings matrix $\mathbf{\Lambda_{h.}}$ Similarly, equation (2) is the measurement model for the standard of living (SoL). The unobserved latent variables *health* and *SoL* are constructed using the indicators described in the next section. Vectors ε_i^h and ε_i^s indicate the measurement error terms.

$$UB_{it} = a'\mathbf{X} + v_{it} \tag{3}$$

$$H_{it} = b_1 UB_{it} + b'\mathbf{Z} + u_{it} \tag{4}$$

$$SoL_{it} = \beta_1 UB_{it} + \beta_2 H_{it} + \beta'\mathbf{W} + e_{it} \tag{5}$$

Model (3)-(5) is the structural equation model of the SEM, where equation (3) explores the determinants of the unemployment benefits *UB* represented by vector **X**, and equation (4) examines the determinants of health including the unemployment benefits and the control variables in vector **Z**. The last equation is the living standards equation where we explore the relationship among health, unemployment and other variables in vector **W** and the living standards. The first step of the SEM is to apply the confirmatory factor analysis (CFA) in the measurement equations (1)-(2), and using the factor loadings we obtain the predicted values derived from the CFA, and these are the *health* and *SoL* indices. In the second step, we include the constructed *SoL* and *health* indices to estimate simultaneously the structural equations (3)-(5). Since we have a panel SEM model, subscript *i* and *t* denote respectively the individual at year-wave of the survey (see for more details Bollen and Brand, 2010).

We could argue that random effects SEM allows for the estimation of the time-invariant observed variables, such as gender, religion and race among others. However, we prefer the fixed effects SEM for various reasons. First, as in the random effects case, panel data may increase the estimation precision, as a result of increase in the number of observations. Nevertheless, we need to control also for correlation in the regression model and the standard errors in the pooled OLS regression are typically underestimated and the *t-statistics* are inflated. Second, fixed effects model allows for unobserved individual heterogeneity and omitted-variable bias, as this heterogeneity can be correlated with the regressors. Thus, instead of using instrumental variables approach, in which is quite difficult to find a valid instrument, the fixed effects may provide an alternative way to this issue if we assume the unobserved individual-specific effects be additive and time-invariant. Moreover, we do not observe time-invariant variables in our data, and in particular in the ILCS, except for gender.

For the equation (3) and the unemployment benefits we will include as control variables the age, education level, marital status, household type, house tenure and the household income reduced by the level of unemployment allowance. The unemployment benefits, as we present in the next section, is a dummy taking a value of 1 for those who receive the allowance and 0 otherwise. In equation (4), which is the health equation, besides the unemployment benefits dummy variable, we include the same control variables, as in equation (3). However, in this case we consider the household income reduced by unemployment benefits and also, sickness and disability benefits, as the latter are effects of poor health and not causes-determinants. In the standard of living (SoL) equation (5), we include the same control variables as in health equation, but we exclude the house tenure, since related variables are used to construct the *SoL* index.

3.3 Fuzzy Regression Discontinuity Design (FRDD) within the SEM Framework

The objective of this section is to present the FRDD within the SEM framework in order to study the effect of unemployment benefits on health and living standards. In particular, employment and working hours are unlikely to be independent from employment decisions. Therefore, to identify the effect of unemployment benefits on health and living standards, we exploit the exogenous variation in the probability of receiving unemployment benefits due to the discontinuity in individual's eligibility of receiving the benefits, which is 600 days in the last three years. Since, the working-employment history in the Income and Living Conditions Survey (ILCS) is recorded in monthly frequency, we convert the 600 days to months, which is equivalent to 20 months. The RDD approach has several advantages discussed in earlier studies (Imbens and Lemieux, 2007; Van der Klaauw, 2008; Lee and Lemieux, 2010). Essentially, because individuals are close to the cut-off or on the two sides of the eligibility period cut-off point, are likely to be very similar. To recall, apart from the 600 days required for someone to be eligible to unemployment benefits we additionally consider individuals who had accumulated at least 120 working days in the last year. Therefore, every individual in our sample has accumulated this amount of days, but the cut-off point takes place only in the case of the 600 days.

RDD is the closest to a randomised experiment trial that can be applied in non-experimental settings, such as the empirical analysis relies on the ILCS. Furthermore, this approach requires fewer assumptions compared to other techniques, with the most common method being the differences-in-differences (DID) method, which relies on identifying a control group very similar to the treatment group. In the case of a "sharp" RDD assuming that the cut-off point is 20 months and considering the structural equations (4)-(5) we have the following:

$$H_{it} = b_1 D_{i,t} + f(UBE_{i,t} - c, a) + D_{i,t} * f(UBE_{i,t} - c, a) + b'\mathbf{Z} + u_{it} \tag{6}$$

$$SoL_{it} = \beta_1 D_{i,t} + f(UBE_{i,t} - c, a) + D_{i,t} * f(UBE_{i,t} - c, a) + \beta_2 H_i + \beta'\mathbf{W} + e_{it} \tag{7}$$

System (6)-(7) is the same with the structural equations (4)-(5), with the difference that we include the dummy variable D, indicating whether individuals are below (D_i = 0) or above (D_i = 1) the threshold of 20 months. The measurement equations (1)-(2) also remain the same, where the CFA is applied to construct the *health* and SoL indices used in equations (6)-(7). Term $f(UBE_{it} - c, a)$ refers to the functional form of the forcing variable *UBE*, which is the period in months and it stands for the unemployment benefits eligibility, and the threshold c, which corresponds to 20 with parameters a. As we mentioned earlier, the eligibility conditions determine how much individuals should have contributed to the funding of the scheme through a minimum employment record to be entitled to claim the unemployment benefits. Like in most countries, the eligibility conditions are defined in a binary way where the workers are entitled to claim these benefits when they reach the threshold of 600 days. This discontinuity may influence not only the workers' labour supply, but also can be internalized by employers, who can align the length of work contracts with the minimum record employment terms. Indeed, when the activity slows down, employers may rely on unemployment insurance to provide employees with a replacement income between two contracts, all the more so if they know that eligibility requirements are not restrictive. In this setting, the fuzzy RDD can be more qualified in the sense that the probability to receive the unemployment benefits does not jump from 0 to 1 for workers with more than 20 months of employment history. Indeed, completing the minimum requirement of 20 months of employment over the past three years, does not imply that the persons will immediately claim the benefits, as the workers may not be informed about their eligibility; they may quickly transit to another job or they may be aware and informed about the benefits, but they prefer to not take the benefits for various reasons, such as stigma (Baumberg Geiger, 2016). Furthermore, the fuzzy RDD is a more suitable approach to include also those who were continuously working less than 120 days over the past year.

Analytically, the estimation of the treatment effect in a fuzzy RDD is often carried out by the two-stage least squares (2SLS) method. Nevertheless, since we have a system of equations to be estimated simultaneously, the SEM-FRDD has a similar setting with the three-stage least squares (3SLS) method, but we include additionally the measurement equations (1)-(2). The SEM-FRDD will become:

$$\mathrm{T}_{it} = \gamma_1 D_{i,t} + f(UBE_{i,t} - c, a) + \gamma'\mathbf{Z} + u_{it} \tag{8}$$

$$\mathrm{H}_{it} = b_1 \hat{T}_{i,t} + f(UBE_{i,t} - c, a) + b'\mathbf{Z} + u_{it} \tag{9}$$

$$SoL_{it} = \beta_1 \hat{T}_{i,t} + f(UBE_{i,t} - c, a) + \beta' \mathbf{W} + e_{it} \quad (10)$$

Where the variables are defined as in the SEM equations (1)-(5) and the RDD equations (6)-(7), except for the variable *T*, which is the actual participation in the unemployment benefits scheme taking a value of 1 if the respondent receives the unemployment benefits and 0 otherwise. In particular, the equation (8) is the first stage regression where we regress the participation variable *T* on the variable *D*, defined as in (6)-(7). Then in the next stage, the fitted values of variable *T* are included in the structural equations (9)-(10). Thus, the SEM-FRDD comprises of the measurement equations (1)-(2) and (8)-(10). We allow for a range of specifications for the months of unemployment function $f(UBE_{it} - c, a)$, including linear and quadratic terms, but only the linear term is significant. We will estimate the FRDD using bandwidths of size 2-5 months and the full sample.

4. Data

The empirical work relies on data derived from the panel ILCS in the period 2007-2015 provided by the Turkish Statistical Institute (TURKSTAT). The ILCS is an annual panel survey, which includes a personal and a household questionnaire and its aim is to collect information that will allow for illustration and comparison of the income distribution between individuals and households, to measure the living conditions, poverty based on monetary and non-monetary dimensions and social exclusion. The survey provides rich information on individual characteristics, such as gender, age, education, health, income and employment status among others, and household characteristics, including material deprivation, social benefits, income, house tenure status, dwelling and environment characteristics.

ILCS is available as a four year rotating panel, and for our analysis there are six waves of panel data compiled: 2007-2010, 2008-2011, 2009-2012, 2010-2013, 2011-2014, and 2012-2015. This means that households are interviewed for four consecutive years. Approximately one fourth of the sample is freshly added each year by replacing the households that were surveyed four times with new ones. The number of new households is selected in order to keep the sample size more or less the same, to reflect the number of households successfully interviewed in the previous year.

In table 1, we report the descriptive statistics for the main outcomes and the number of independent variables employed in the empirical analysis. As we have discussed in the methodology section, SEM consists of two main latent variables, health and living standards. In table 1, we present the three observed variables used to create the health index, where have been converted into dummy variables taking value 1 for healthy state and 0 for unhealthy state. The variables used for the *SoL* index are constructed taking value 1 on whether the household does not face any particular financial problem. More specifically, regarding the questions on financial burden and arrears, we define as 1 the households do not report any financial burden related to housing costs or debts and also those households with no arrears on mortgage or utility bills. Regarding the capacity of the households to afford holiday, unexpected financial expenses, or meat-fish every second day in a row if required, we define a value of 1 for those who can afford related expenses and 0 otherwise. Therefore, in this case a positive sign of the estimated coefficients of any variable will indicate an improvement in living standards. Another set of potential variables used to construct the living standards index is durable goods, such as whether the households has a car, kitchen, computer internet connection, mobile phone, air conditioner and others. However, since we explore the impact of unemployment benefits, durable goods could have been probably purchased a long time ago. Thus, as we do not have the information of the date of purchase, we prefer to consider only the indicators reported in panel A of table 1 for the standard of living index.

In panel A of table 1, we report the average and standard deviation of the observed variables used to construct the health and living standard indices, while the minimum and maximum values are always 0 and 1 respectively. In panels B and C, we report the summary statistics for the control variables. The proportion of people receiving the unemployment schemes in our sample is 3.61 percent. We will not thoroughly discuss the rest of the control variables, including the marital status, education level and house tenure, but we report those in table 1 to show that the majority of the respondents is either single or married, own the house and have completed the primary school.

5. Empirical Results

In table 2, we report the estimates of the main SEM system (1)-(5), where in the first column we present the unemployment benefits regressions, while in columns (2)-(3) we report respectively the estimated coefficients for the health and *SoL* equations. We should recall that in table 2 we consider the dummy of unemployment benefits, taking a value of 1 for those who receive the benefits and 0 otherwise. In panel A, it becomes apparent that households receiving these benefits enjoy higher levels of wealth (living standards) and an improvement in health. As it was expected, good health conditions improve the living standards by 0.076, while the household income excluding the unemployment benefits improves both health and standard of living.

Regarding the estimated coefficients of the control variables, we observe that educated people enjoy higher levels of living standard and better health outcomes. Regarding marital status, widowed and divorced experience lower levels of health, which can be attributed to age, especially for widowed who consist mainly of the elder people. On the other hand, married people present higher levels of living standards compared to singles. Households consisting of 2 adults with no dependent children report lower levels of living standards, while households with 2 adults and one or two dependent children are wealthier. One explanation may lie in the fact that wealthier households may decide to have more children, while on the other hand, we could argue that larger households may experience additional expenses. Nevertheless, the main aim of the study is to explore the relationship among unemployment benefits, health and living standards, while further investigation of the remained variables can be extended in future studies.

Following Komada et al. (2019) and Shahidi et al. (2019) we conducted sensitivity analyses in which we stratified the main SEM model by gender, income and education groups. In particular, we estimate the SEM system by men versus women respectively in panels A and B of table 3, while in panels C and D we report the estimates by education level. In this case, we define those who have completed up to a secondary school as low educated, and as high education we define those who have completed the high school and over, including vocational schools and tertiary education. For the income we have taken the deciles and the low income group includes households whose income belongs to the bottom five deciles, versus the high income households that belong to the top five deciles of the income. The stratification of the models by key socio-economic groups allows us to explore the heterogeneity in treatment effects, while simultaneously we are able to minimise the influence of these variables as possible sources of confounding. In table 3 we repeat the SEM estimates of the system of equations (1)-(5). We observe that men who receive the unemployment benefits report higher levels of health and living standards compared to their female counterparts. Even more, we find an insignificant effect of the unemployment benefits on women's health status, even though the latter has a large influence to the living standards compared wot men's sample. This is supported from previous studies that have found men are more likely to be negatively affected by unemployment (Gulliford et al., 2014), while men who are unemployed and do not receive unemployment benefits are more likely to report lower levels of mental health (Artazcoz et al., 2004), affecting consequently their living standards.

In panels C and D of table 3, we report the estimates respectively for high and low educated persons, and we observe that unemployment benefits have a higher positive effect on health and *SoL* of low educated people, while the estimated coefficient of unemployment benefits on the structural equation of the latent variable *health* of the high educated persons is insignificant. A similar conclusion is derived from the estimates across income groups in panels E and F, in which we find a higher impact of unemployment benefits on the *SoL* of the low income group, while the impact of unemployment benefits on the individuals' health status that belong to the high income group is insignificant. Our results are consistent with the findings by (Shahidi et al., 2019) who found a significant positive association between unemployment benefit recipiency and self-rated health among less educated and lower income individuals, while an insignificant treatment effect is found among their more educated and higher income counterparts. These results suggest that the health and *SoL* effects of unemployment benefits, while are strongly protective among more socio-economically disadvantaged individuals, can be small or even negligible among the less socio-economically disadvantaged individuals, indicated by the lower coefficients in the *SoL* equation and the insignificant coefficients in the health equation.

The second part of the analysis is the SEM-FRDD where we use the number of days required to be eligible for the unemployment benefits scheme as the cut-off point, discussed in the previous section. In panel A of table 3, we present the estimates for the SEM-FRDD system (8)-(10) and the cut-off point of 20 months of employment over the last 3 years. We choose a bandwidth of 2 to 5 months, corresponding to 60, 90, 120, 150 days below and above the threshold, as well as, we estimated the SEM-FRDD using the full sample. Higher polynomial orders in the RDD are found insignificant, and in particular the term $f(UBE_{i,t} - c, a)$, therefore, we present the estimates for the linear terms only. In figures 1 and 2, we illustrate the RDD graphs respectively for health and standard of living index, which are standardized. We observe a significant jump upwards on the right side of the cut-off point in figure 1, indicating a better health status for the "treated". Similarly, in figure 2 we observe a significant jump upwards around the cut-off point of 20 months, implying that individuals who are eligible for unemployment benefits may improve their living standards.

In table 4 we present the SEM-FRDD results and we observe that the full sample estimates are similar to those found in table 2. In particular, according to the SEM-FRDD, respondents who receive the unemployment benefits are more likely to improve their health status and living standards respectively by 0.45 and 0.16, compared to 0.40 and 0.15 found using the SEM. The results remain relatively stable when we consider the bandwidths of 2-5 months of employment which correspond to 22 to 25 months of employment on the right side of the cut-off point and 15 to 18 months on the left side. As a diagnostic test we report the *F-statistic* test of the first stage regression (8) and based on the *p-values* we reject the null hypothesis concluding that the instrument is not weak. Similarly, we present the *Hausman t-test* and its associated *p-values*, and we can see that in all cases we accept the null hypothesis of no endogeneity.

In table 5 we follow a similar approach to the estimates of table 3, where we repeat the SEM-FRDD estimates by gender, education and income groups. The main concluding remarks remain the same, as the unemployment benefits have a considerable higher impact on the health status and living standards of men at 0.055 and 0.188 respectively compared to their female counterparts at 0.047 and 0.129 respectively. Similarly, the impact of unemployment benefits is higher on the health status of low educated persons at 0.048 compared to high educated people at 0.030, while the impact is slightly higher on the *SoL* of low educated workers. Regarding the results across income groups we find that the unemployment benefits have no impact on the health status of high income individuals, and a considerable effect on low income individuals' health status is found. Finally, the impact on the living standards of low income workers is almost 37 percent higher compared to the *SoL* of their high income counterparts. Our findings are consistent with the study by Shahidi et al. (2019) who explore the impact of unemployment benefits on health, however, we extend our analysis to consider also the *SoL*.

Motivated by the preliminary tests on the validity of the RDD estimates and to analyse the effects from the local randomization inference estimation, we run placebo regressions as a robustness check. In order to eliminate the possibility that the estimated treatment impact reflects a difference in the health and *SoL* outcomes explored between individuals just above and below, as well as, over the full sample, and the potential role of the treatment confoundedness, we estimate separately the SEM-FRDD for formal and informal workers. In particular, the unemployment benefits are given only to workers employed in the formal sector, thus, we should expect to find no discontinuities in the sample of the informal workers. In table 6 we report the estimates considering the sample of the formal workers in panel A, and those employed in the informal sector in panel B. We find no discontinuity in the second sample, indicated by the insignificant coefficient of b_1 (T) in both full and within the various bandwidth samples.

6. Conclusions

In this study we attempted to investigate the impact of unemployment benefits on health and living standards using the SEM approach, while we also proposed a Fuzzy RDD within the SEM framework. The findings suggest a positive impact of the social benefits on both health and the households' standard of living. Furthermore, the unemployment benefits are more protective for males, low educated and lower income individuals. Women are less likely to receive unemployment benefits, and they report lower levels of health and living standards, thus, these benefits are not enough to provide the same protection as they do for men. The main explanation is that female labour force participation rates, as well as, the employment in the formal sector- which can be caused by gender roles and social norms and discrimination, apart from other reasons- are considerable lower compared to men, highlighting the large discrepancies between the two sexes. This is a barrier for women to be eligible for this type of benefit scheme, which translates to the lower impact of those benefits on their health and *SoL*. On the other hand, unemployment benefits seem to offer a higher protection for low educated and low income groups.

The results indicate that the association between poor health and unemployment may partly result from the loss of income after job loss (Bartley, 1994; Janlert and Hammarstrom, 2009). Although income is not likely to be the only mechanism by which unemployment affects health, our findings illustrate and highlight the potential of income support programmes, not only to smooth consumption during periods of unemployment, as indicated in the literature (Gruber, 1997), but also to affect health after job loss.

However, the study is not without drawbacks. One issue is the small sample size of those who are eligible for the certain type of social benefits explored, which may limit the robustness of the findings. Furthermore, another issue is that SEM within fixed effects cannot capture other time-variant characteristics that may influence health and living standards. The third issue is about the validity of our FRDD estimates. Nevertheless, we have attempted to address this issue by applying the FRDD to account for potential manipulation on the assigning variable. The results remain robust when we consider both full sample and the samples within various bandwidths. Another issue is that we do not control for the health conditions of other household members. While we could account for these characteristics, we preferred to not include only the married couples, since almost the 50 percent of the sample is singles. Even though we have information about the parents and other relatives of the singles, we have also a large proportion of singles and divorced living alone. Hence, limiting the sample only to those living with other household members we may create a selection bias. Nevertheless, since this is out of the study's current topic, we propose future studies to explore also the role and health status of other household members and to investigate possible inter-household and intra0household inequalities.

Concerns about the job destruction and unemployment increases the demand for social insurance, which in our case is the unemployment benefits. While the findings suggest this social insurance scheme may cushion the negative effects of the job loss in terms of health and living standards, according to previous studies, it may have a negative side effect which is the decreasing incentive to find a new job (Atkinson and Micklewright, 1991; Ortega and Rioux, 2010; Corsini, 2011). Thus, it is important to set up an unemployment benefits scheme having a structure that minimises the disincentive of looking for a job, but also provides insurance to individuals and households to smooth their consumption, and protect them from poverty traps and health negative shocks. Furthermore, policies that encourage female labour participation, as well as, the employment in the formal sector for women, should be prioritized and implemented to reduce the large discrepancies in the labour market between men and women.

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Figure 1. SEM-FRDD Estimates for Health

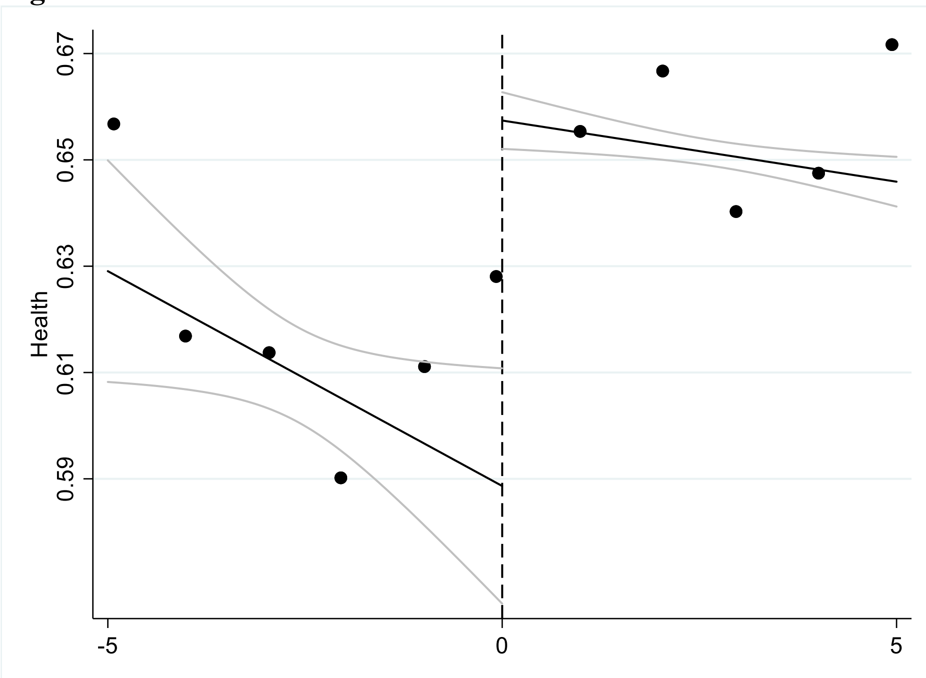

Figure 2. SEM-FRDD Estimates for SoL

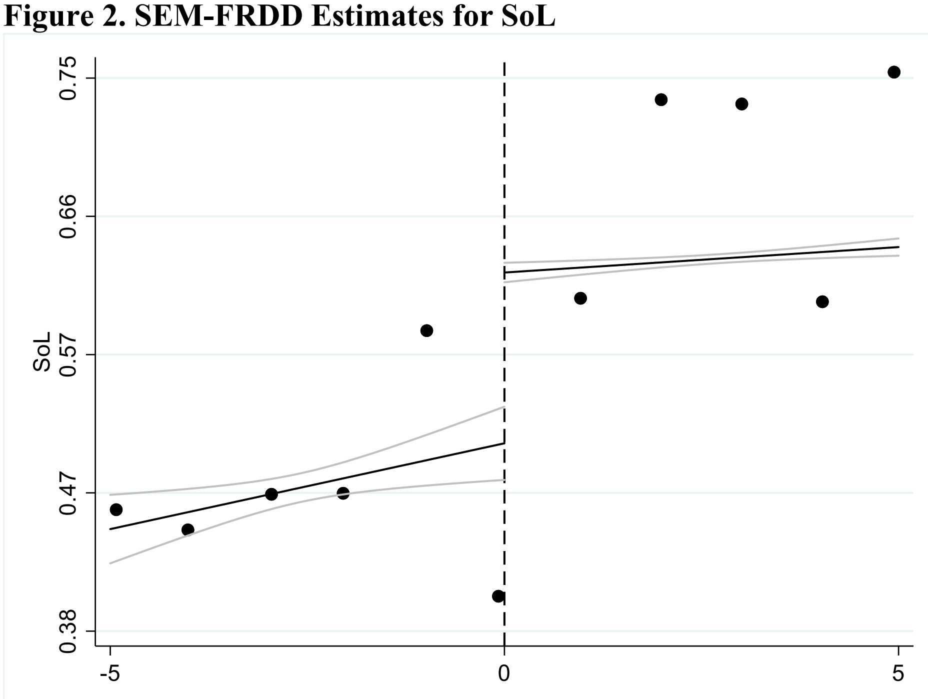

Table 1. Summary statistics

Variables	Mean	Standard Deviation	Minimum	Maximum
Panel A: Latent variables				
Health Index				
Health Status (1 for good and very good)	0.8605	0.3446	0	1
Suffer from any a chronic (long-standing) illness or condition (No)	0.6314	0.4824	0	1
Health limitations (No)	0.7319	0.4429	0	1
Standard of Livings Index				
Arrears on mortgage, loan repayments or rent payments in the last 12 months (No)	0.7172	0.4503	0	1
Arrears on utility bills in the last 12 months (No)	0.6948	0.4604	0	1
Arrears on hire purchase instalments, credit cards or other loan payments in the last 12 months (No)	0.6969	0.4595	0	1
Financial burden of the repayment of debts from hire purchases or loans excluding housing costs (No)	0.0683	0.2524	0	1
Financial burden of the total housing cost (No burden)	0.1644	0.3706	0	1
Capacity to afford paying for one week whole household annual holiday away from home if needed or required (Yes)	0.1975	0.3981	0	1
Capacity to afford a meal with meat, chicken, fish (or vegetarian equivalent) every second day if needed (Yes)	0.5157	0.4997	0	1
Capacity to face unexpected financial expenses (Yes)	0.4899	0.4998	0	1
Ability to keep home adequately warm (Yes)	0.7215	0.4482	0	1
Ability to Make Ends Meet with total monthly household Income (Easily)	0.3686	0.3935	0	1
Panel B: Unemployment and Continuous Control Variables				
Unemployment Benefits (Receive)	0.0361	0.1119	0	1
Annual Unemployment Benefits-Allowance	2,341.361	2,514.62	100.73	19,201.29
Annual Household Income	27,402.78	23,943.64	0	642,017.8
Annual Household Income Excluding Unemployment Benefits	27,374.24	23,931.21	0	642,017.8
Annual Household Income Excluding Unemployment, Sickness and Disability Benefits	27,318.84	23,944.96	0	642,017.8
Age	36.619	11.760	15	65
Unemployed	0.0886	0.2768	0	1

Table 1 (Cont.) Summary Statistics

Variables	Proportions	Variables	Proportions
Panel C: Categorical Control Variables			
Marital Status-Never Married	50.92	Education- General high school	9.20
Marital Status- Married	40.40	Education- Vocational or technical high school	7.11
Marital Status-Widowed	2.66	Education- University, College and higher	10.04
Marital Status- Divorced	6.02	House tenure-Owner	65.15
Illiterate	12.86	House tenure- Tenant	19.09
Education-Literate, not finishing a school	8.27	House tenure- Lodging	1.50
Education- Primary school	33.94	House tenure-Other	14.26
Education- Secondary school	18.58		

Table 2. SEM Estimates of the Equation System (1)-(5)

	DV: UB	DV: Health	DV: SoL
Unemployment Benefits		0.0401**	0.1513***
		(0.0164)	(0.0151)
Health			0.0764***
			(0.0032)
Log of Household Income Excluding Unemployment, Disability and Sickness Benefits		0.1180***	
		(0.0032)	
Log of Household Income Excluding Unemployment Benefits	-0.0069***		0.6559***
	(0.0002)		(0.003)
Age	0.2598***	1.0866***	0.3145***
	(0.0131)	(0.0857)	(0.1023)
Age squared	-0.3349***	-0.7751***	-0.2288***
	(0.0168)	(0.1025)	(0.1251)
Marital Status- Married	0.0013	-0.0179***	0.0735***
	(0.0058)	(0.0041)	(0.0051)
Marita l Status- Widowed	0.0025	-0.1146***	-0.1530***
	(0.0019)	(0.0119)	(0.0115)
Marital Status- Divorced	0.0035	-0.1044***	-0.0968***
	(0.0027)	(0.0125)	(0.0110)
Education Level-Literate, but not graduate (Reference Illiterate)	0.0019	0.1595***	0.0154
	(0.0014)	(0.0095)	(0.0137)
Education Level-Primary School	0.0094***	0.2770***	0.0455***
	(0.0012)	(0.0072)	(0.0056)
Education Level –Secondary vocational School	0.0134***	0.3146***	0.0494***
	(0.0012)	(0.0084)	(0.0077)
Education Level - General High School	0.0159***	0.3559***	0.1122***
	(0.0014)	(0.0091)	(0.0087)
Education Level –Vocational and technical high School	0.0218***	0.3759***	0.1506***
	(0.0013)	(0.0103)	(0.0089)
Education Level -University and higher	0.0112***	0.3953***	0.3244***
	(0.0013)	(0.0092)	(0.0095)
House Tenure-Tenant (Reference Category Owner)	0.0061***	-0.0022	
	(0.0006)	(0.0045)	
House Tenure-Lodging	-0.0107	-0.0265**	
	(0.0098)	(0.0129)	
Household Type- 2 adults<65 years, no dependent children (Reference Category-Single)	0.0009	-0.0487***	-0.2549***
	(0.004)	(0.0167)	(0.0181)
Household Type-Two adults with one dependent child	0.0019	-0.0187	0.3467***
	(0.0023)	(0.0162)	(0.0182)
Two adults with two dependent children	0.0014	-0.0183	0.4161***
	(0.0021)	(0.0160)	(0.0169)
No Observations	162,398		
AIC	283,802.3		
BIC	284,674.5		

Robust standard errors within parentheses, ***, ** and * indicate significance respectively at 1%, 5% and 10% level. UB denotes unemployment benefits taking a value of 1 if the respondent receives the benefits and 0 otherwise, and SoL denotes standard of living. DV denotes dependent variable while AIC and BIC refer to the Akaike Information Criteria and Bayesian Information Criteria respectively.

Table 3. SEM Estimates of the Equation System (1)-(5) by Gender, Income and Education Groups

Panel A: Males	**DV: Health**	**DV: SoL**
Unemployment Benefits	0.0523**	0.1592***
	(0.0246)	(0.0166)
Health		0.0749***
		(0.0038)
No Observations	113,629	
AIC	206,551.4	
BIC	207,534.7	
Panel B: Females	**DV: Health**	**DV: SoL**
Unemployment Benefits	0.0209	0.1254***
	(0.0360)	(0.0382)
Health		0.0823***
		(0.0055)
No Observations	48,769	
AIC	61,611.66	
BIC	62,508.73	
Panel C: High Education Level		
Unemployment Benefits	0.0223	0.1395***
	(0.0206)	(0.0212)
Health		0.0715***
		(0.0036)
No Observations	57,081	
AIC	86,840.79	
BIC	87,646.49	
Panel D: Low Education Level		
Unemployment Benefits	0.0531**	0.1575***
	(0.0232)	(0.0257)
Health		0.0782***
		(0.0063)
No Observations	105,317	
AIC	183,353.1	
BIC	184,242.6	
Panel E: High Income Level		
Unemployment Benefits	0.0281	0.1318***
	(0.0183)	(0.0223)
Health		0.0867***
		(0.0045)
No Observations	88,289	
AIC	121,591.1	
BIC	122,530.9	
Panel F: Low Income Level		
Unemployment Benefits	0.1065***	0.1604***
	(0.0273)	(0.0227)
Health		0.0662***
		(0.0041)
No Observations	74,109	
AIC	150,071.9	
BIC	151,029.5	

Robust standard errors within parentheses, *** and ** indicate significance respectively at 1% and 5% level.

Table 4. SEM-FRDD Estimates for the System of Equations (1)-(2) and (8)-(10)

	Full Sample		**Bandwidth 2 months**		**Bandwidth 3 months**		**Bandwidth 4 months**		**Bandwidth 5 months**	
	DV: Health	DV: SoL	DV: Health	DV: SoL	DV: Health	DV: SoL	DV: Health	DV: SoL	DV: Health	DV: SoL
b_1 (T)	0.0454** (0.0186)	0.1622*** (0.0266)	0.0579** (0.0263)	0.1474*** (0.0235)	0.0561** (0.0274)	0.1556*** (0.0272)	0.0546** (0.0248)	0.1527*** (0.0258)	0.0557*** (0.0097)	0.1559*** (0.0371)
Health		0.0802*** (0.0054)		0.0796*** (0.0033)		0.0784*** (0.0031)		0.0788*** (0.0028)		0.0792*** (0.0097)
No Obs.	162,398		6,344		8,382		9,552		11,492	
Weak Instrument F-Test	16.892 [0.000]		13.838 [0.000]		11.796 [0.0006]		12.072 [0.0002]		12.624 [0.000]	
Hausman Endogeneity T-Test	-0.445 [0.658]		0.414 [0.682]		0.618 [0.542]		-0.874 [0.385]		-0.342 [0.731]	
AIC	355,330.1		250,345.0		266,334.0		282,299.1		311,375.8	
BIC	356,716.8		251,878.6		267,877.5		283,746.3		312,843.2	

Robust standard errors within parentheses, p-values within brackets, *** and ** indicate significance respectively at 1% and 5% level.

Table 5. SEM-FRDD Full Sample Estimates for the System of Equations (1)-(2) and (8)-(10) by Gender, Education and Income Groups

	Panel A: Gender			
	Males		**Females**	
	DV: Health	DV: SoL	DV: Health	DV: SoL
b_1 (T)	0.0552***	0.1871**	0.0479*	0.1295***
	(0.0128)	(0.0888)	(0.0263)	(0.0293)
Health		0.0793***		0.0868***
		(0.0017)		(0.0112)
No Obs.	113,629		48,769	
AIC	228,453.31		135,213.2	
BIC	230,828.68		135,772.7	
	Panel B: Education			
	High Education Level		**Low Education Level**	
	DV: Health	DV: SoL	DV: Health	DV: SoL
b_1 (T)	0.0302*	0.1592**	0.0483**	0.1663***
	(0.0166)	(0.0694)	(0.0221)	(0.0176)
Health		0.0674***		0.0865***
		(0.0188)		(0.0051)
No Obs.	57,081		105,317	
AIC	340,722.4		253,462.7	
BIC	340,983.7		253,364.4	
	Panel C: Income			
	High Income Level		**Low Income Level**	
	DV: Health	DV: SoL	DV: Health	DV: SoL
b_1 (T)	0.0362	0.1229***	0.0659***	0.1680***
	(0.0256)	(0.0161)	(0.0129)	(0.0310)
Health		0.0855***		0.0661***
		(0.0069)		(0.0051)
No Obs.	88,289		74,109	
AIC	249,039.4		298,114.3	
BIC	248,547.4		297,645.2	

Robust standard errors within parentheses, ***, ** and * indicate significance respectively at 1%, 5% and 10% level.

Table 6. SEM-FRDD Falsification Test for the System of Equations (1)-(2) and (8)-(10)

	Panel A: Formal Workers									
	Full Sample		**Bandwidth 2 months**		**Bandwidth 3 months**		**Bandwidth 4 months**		**Bandwidth 5 months**	
	DV: Health	DV: SoL	DV: Health	DV: SoL	DV: Health	DV: SoL	DV: Health	DV: SoL	DV: Health	DV: SoL
b_1 (T)	0.0465**	0.1841***	0.0631*	0.1894**	0.0654**	0.1857**	0.0617***	0.1846***	0.0529***	0.1930***
	(0.0188)	(0.0352)	(0.0331)	(0.0871)	(0.0269)	(0.0885)	(0.0161)	(0.0551)	(0.0152)	(0.0443)
Health		0.0858***		0.0832*		0.0820**		0.0762**		0.0809***
		(0.0139)		(0.0463)		(0.0376)		(0.0348)		(0.0241)
No Obs.	105,104		3,832		4,908		6,756		8,520	
AIC	325,905.7		230,068.6		245,648.3		274,206.9		289,814.5	
BIC	326,329.4		230,523.2		246,532.5		275,111.4		290,317.2	
	Panel B: Informal Workers									
	Full Sample		**Bandwidth 2 months**		**Bandwidth 3 months**		**Bandwidth 4 months**		**Bandwidth 5 months**	
	DV: Health	DV: SoL	DV: Health	DV: SoL	DV: Health	DV: SoL	DV: Health	DV: SoL	DV: Health	DV: SoL
b_1 (T)	0.0325	0.0362	0.0528	0.0438	0.0495**	0.0373	0.0572	0.0188	0.0532	0.0162
	(0.0254)	(0.0288)	(0.0471)	(0.0355)	(0.0378)	(0.0415)	(0.0484)	(0.0205)	(0.0487)	(0.0277)
Health		0.0663***		0.0727**		0.0714**		0.0786***		0.0757***
		(0.065)		(0.0332)		(0.0336)		(0.0127)		(0.0127)
No Obs.	57,294		2,512		3,474		2,796		2,972	
AIC	392,119.2		241,557.6		258,162.4		278,234.9		294.280.2	
BIC	392,659.5		241,594.4		258,614.5		278,725.4		294,779.6	

Robust standard errors within parentheses, ***, ** and * indicate significance respectively at 1%, 5% and 10% level. SoL denotes standard of living. DV denotes dependent variable, while AIC and BIC refer to Akaike Information Criteria and Bayesian Information Criteria respectively.